2 Müntz-Jackson Theorems

Recall:

• Density properties of Müntz polynomials.

Theorem (Theorem 1.1 in [Lorentz (1996)]).

Let $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \infty\}$ with $\lambda_n \to \infty$. Then the Müntz space $\mathcal{M}(\Lambda_{\infty})$ is dense in each of the spaces C[0,1] or $L_p[0,1]$, $1 \le p < \infty$ if and only if

$$\sum_{k=1}^{\infty} \frac{1}{\lambda_k} = \infty.$$

The density property can be indeed extended in several ways: unsorted sequences (which may result in distinct cluster points), complex sequences, and intervals away from the origin.

Under this iff condition, the sequence Λ_{∞} can be generalized as

$$\begin{cases} \lambda_0 \geqslant 0 \text{ and } \{\lambda_k\}_{k=1}^{\infty} \text{ with } \inf_{k\geqslant 1} \{\lambda_k\} > 0, & \text{for } L_p[0,1] \text{ with } 1\leqslant p < \infty; \\ \lambda_0 = 0 \text{ and } \{\lambda_k\}_{k=1}^{\infty} \text{ with } \inf_{k\geqslant 1} \{\lambda_k\} > 0, & \text{for } C[0,1] \text{ with } p = \infty. \end{cases}$$

But its proof requires some techniques and discussions in the cases of distinct cluster points (see [Borwein (1995), Sec. 4.2] or [Almira (2007), Sec. 3.1]).

• L_p -Best Approximation by Müntz Polynomials. Let $f \in L_p[0,1]$ if $1 \leq p < \infty$ (or C[0,1] if $p = \infty$). The error of approximation from $\mathcal{M}(\Lambda_n)$ to f is

$$E(f, \Lambda_n)_p := \inf_{M \in \mathcal{M}(\Lambda_n)} ||f - M||_{L_p[0,1]}.$$

Note that C[0,1] with L_{∞} -norm is completed since it reduces to **maximum norm**. In fact, when $p = \infty$, for $f \in C[0,1]$ we have

$$||f||_{\infty} := \inf\{C : |f(x)| \leqslant C \text{ a.e. on } [0,1]\} = \inf_{\substack{mF_0 = 0 \\ F_0 \subset [0,1]}} \left\{ \sup_{x \in [0,1] \setminus F_0} |f(x)| \right\} = \max_{0 \leqslant x \leqslant 1} \{|f(x)|\},$$

where $mF_0 = 0$ denotes that the Lebesgue measure of F_0 is 0.

Schedule:

We consider the L_p best approximation (or Jackson Theorems in Sec. 2) in several subsections:

- 1. Existence and uniqueness of L_p best approximation.
- 2. Error of approximation for monomial x^r , and dense properties.
- 3. Error of approximation for $f \in W_p^1[0,1]$, and some corollaries.

Notation Convention:

- AuxThm refers to the auxiliary theorem, which is not included in this book, similar to AuxCor, AuxLem, and other related terms.
- Denote $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \dots\}$ with $\lim_{n \to \infty} \lambda_n = \infty$.
- Denote $\Lambda_n = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n\}$ simply by Λ , where the integer $n \ge 1$ is fixed.
- Denote the linear space $\mathcal{M}(\Lambda_n) = \operatorname{span}\{x^{\lambda_0}, \dots, x^{\lambda_n}\}$, associated to Λ_n , with respect to the field of real numbers \mathbb{R} .
- $E(f, \Lambda_n)_p = \inf_{M \in \mathcal{M}(\Lambda_n)} \|f M\|_p$, where $\|\cdot\|_p$ stands for the $L_p[0, 1]$ norm for $1 \leq p \leq \infty$.

2.1 Existence and uniqueness of L_p -best approximation.

Let $(X, \|\cdot\|)$ be a Banach space with **real or complex** scalars, and $X_n \subset X$ be its finite dimensional linear subspace. The *best approximation* to $f \in X$ from X_n is defined as

$$E(f) := \inf_{p \in X_n} ||f - p||.$$

AuxThm 2.1 (Theorem 1.1, p.59, [Lorentz (1993)]). For each $f \in X$, there exists a best approximation to f from X_n .

Proof. Let F(p) = ||f - p||, $\forall p \in X_n$. Let the **closed and bounded** set $C = \{p \in X_n : F(p) \leq ||f||\}$. Then that F(p) attains its minimum over X_n is equivalent to attain the minimum over C, that is

$$\inf_{p \in X_n} \|f - p\| = \inf_{p \in C} \|f - p\|.$$

Thus the existence is obvious since C is **compact** and F(p) is **continuous**.

AuxThm 2.2. If X is strictly convex, which is characterized by

$$\left\{ \begin{array}{ll} \forall f_1 \neq f_2, & \|f_1\| = \|f_2\| = 1, \quad \alpha_1, \alpha_2 > 0, \quad \alpha_1 + \alpha_2 = 1, \\ imply & \|\alpha_1 f_1 + \alpha_2 f_2\| < 1. \end{array} \right.$$

Then the best approximation to $f \in X$ from X_n is unique.

Proof. Suppose that there are $p_1, p_2 \in X_n$ such that $||f - p_1|| = ||f - p_2|| = E(f)$. If E(f) = 0, then $||p_1 - p_2|| \le ||f - p_1|| + ||f - p_2|| = 2E(f) = 0$, which implies $p_1 = p_2$. If E(f) > 0, we prove it by supposing that $p_1 \ne p_2$, which leads to a contradiction:

$$E(f) \le \left\| f - \frac{1}{2}(p_1 + p_2) \right\| = \left\| \frac{1}{2}(f - p_1) + \frac{1}{2}(f - p_2) \right\| < E(f).$$

AuxLem 2.1. $L_p[a,b]$ is strictly convex for 1 .

Proof. For any $f_1 \neq f_2$, $||f_1||_p = ||f_2||_p = 1$, $\alpha_1, \alpha_2 > 0$, $\alpha_1 + \alpha_2 = 1$, then by Minkowski's inequality (or triangle inequality):

$$\|\alpha_1 f_1 + \alpha_2 f_2\|_p < \alpha_1 \|f_1\|_p + \alpha_2 \|f_2\|_p = 1.$$

The equality for $1 if and only if <math>f_1$ and f_2 are **positively linearly dependent**, that is, $f_1 = \lambda f_2$ for some $\lambda \ge 0$ or $f_2 = 0$. This is impossible since $f_1 \ne f_2$ and $||f_1|| = ||f_2|| = 1$. \square

Remark 2.1. Both $L_1[a,b]$ and $L_{\infty}[a,b]$ are **not** strictly convex.

Remark 2.2. When we consider vectors in \mathbb{R}^2 , the strictly convex property for L_p is visualizable. Let $\mathbf{x} = [x_1, x_2]$.

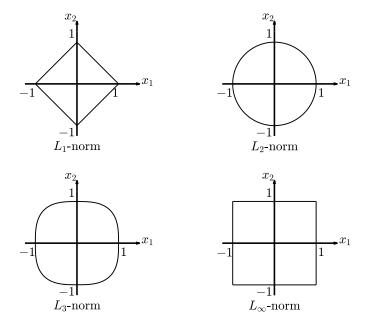


Figure 1: Unit circles in \mathbb{R}^2 with different L_p -norms. Download the Figure and Code.

AuxThm 2.3. Let X = C[a, b] and $X_n \subset X$ satisfy the **Haar condition**:

For any basis $\{\phi_i(x)\}_{i=1}^n$ of X_n and any set of distinct points $\{\xi_i\}_{i=1}^n \subset [a,b]$, it follows that

$$\begin{bmatrix} \phi_1(\xi_1) & \cdots & \phi_1(\xi_n) \\ \vdots & & \vdots \\ \phi_n(\xi_1) & \cdots & \phi_n(\xi_n) \end{bmatrix} \text{ is non-singular.}$$

Then for any $f \in X$, there is just one L_1 (or L_{∞}) best approximation to f from X_n .

Proof. The L_1 -best approximation, see [Powell (1981), Theorem 14.3, p.170], while L_{∞} -best approximation, see [Powell (1981), Theorem 7.6, p.80].

2.2 Error of approximation for monomial x^r .

Schedule of this Subsection:

- Prove that $E(x^r, \Lambda)_2$ (Eq. (2.1)) and $\mathcal{M}(\Lambda_{\infty})$ is dense in $L_2[0, 1]$;
- Prove that $E(x^r, \Lambda)_{\infty}$ (Eq. (2.2)) and $\mathcal{M}(\Lambda_{\infty})$ is dense in C[0, 1];
- Prove that $E(x^r, \Lambda)_p$ $(2 (Theorem 2.2) and <math>\mathcal{M}(\Lambda_\infty)$ is dense in $L_p[0, 1]$.

2.2.1 Case 1: p = 2.

Our goal is to prove (2.1) in [Lorentz (1996)], which is stated as following theorem:

AuxThm 2.4 (see also Theorem 5.4 in [Lorentz (1993)]). For r > -1/2, $\Lambda = {\lambda_0, \lambda_1, \dots, \lambda_n}$ with distinct elements and $\lambda_k > -1/2$, $k = 0, 1, \dots, n$, we have

$$E(x^r, \Lambda)_2 = \frac{1}{\sqrt{2r+1}} \prod_{k=0}^n \frac{|r - \lambda_k|}{|r + \lambda_k + 1|}.$$

Preliminaries.

In a **real** Hilbert space $(H, (\cdot, \cdot))$ with its norm induced by $||f|| = \sqrt{(f, f)}$, let $f_1, \dots, f_n \in H$ be linearly independent elements, and let $X_n := \text{span}\{f_1, \dots, f_n\}$.

AuxThm 2.5. For $g \in H$, there is a unique $f \in X_n$ such that

$$||g - f|| = \inf_{p \in X_n} ||g - p||.$$

Proof. Existence is obvious and uniqueness follows from that Hilbert space is strictly convex, see details. \Box

We call f the best approximation of g from X_n in H.

AuxCor 2.1. Let f be the best approximation of g, then it is equivalent to the orthogonal projection: (g - f, p) = 0, $\forall p \in X_n$.

Proof. (\Leftarrow) Let f be the orthogonal projection of g onto X_n , i.e., (g-f,p)=0, $\forall p \in X_n$. Then $\|g-p\|^2 = \|g-f+f-p\|^2 = \|g-f\|^2 + \|f-p\|^2 \geqslant \|g-f\|^2$.

Thus f is the best approximation.

 (\Rightarrow) Let f satisfy $||g-f|| = \inf_{p \in X_n} ||g-p||$. For any $p \in X_n$, let

$$h(t) = ||g - (f + tp)||^2 = ||g - f||^2 - 2t(g - f, p) + t^2||p||^2$$

Since h(t) achieves its minimum at t=0, then h'(0)=0, which leads to (g-f,p)=0.

AuxLem 2.2. The distance of best approximation $d := \inf_{p \in X_n} \|g - p\|$ is given by

$$d^2 = \frac{G(g, f_1, \cdots, f_n)}{G(f_1, \cdots, f_n)},$$

where G is the Gram determinant

$$G(f_1, \dots, f_n) = \left| \begin{array}{ccc} (f_1, f_1) & \cdots & (f_1, f_n) \\ \vdots & & \vdots \\ (f_n, f_1) & \cdots & (f_n, f_n) \end{array} \right|.$$

Proof. The best approximation $f \in X_n$ to g satisfies (g - f, p) = 0, $\forall p \in X_n$. Now we suppose that $f = \sum_{i=1}^n a_i f_i$, then

$$\sum_{i=1}^{n} a_i(f_i, f_k) = (g, f_k), \quad k = 1, 2, \dots, n.$$
 (1)

On the other hand, since (g-f,f)=0, $d^2=(g-f,g-f)=(g,g-f)=(g,g)-(g,f)$, we have

$$\sum_{i=0}^{n} a_i(g, f_i) = (g, g) - d^2.$$
(2)

Hence combining (1) with (2) we have

$$\begin{bmatrix} 1 & (g, f_1) & \cdots & (g, f_n) \\ 0 & (f_1, f_1) & \cdots & (f_n, f_1) \\ \vdots & \vdots & & \vdots \\ 0 & (f_1, f_n) & \cdots & (f_n, f_n) \end{bmatrix} \begin{bmatrix} d^2 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} (g, g) \\ (g, f_1) \\ \vdots \\ (g, f_n) \end{bmatrix},$$

and by Cramer's rule,

$$d^2 = \frac{G(g, f_1, \cdots, f_n)}{G(f_1, \cdots, f_n)}.$$

Remark 2.3. $G(f_1, \dots, f_n) \neq 0$ if and only if f_1, \dots, f_n are linearly independent.

Remark 2.4. AuxThm 2.5, AuxCor 2.1, and AuxLem 2.2 provide a general framework to compute error estimation of best approximation in a Hilbert space.

AuxLem 2.3 (Cauchy's determinant). For real numbers a_i and b_k that satisfy $a_i + b_k \neq 0$, $1 \leq i, k \leq n$, we have

$$\begin{vmatrix} \frac{1}{a_1+b_1} & \cdots & \frac{1}{a_1+b_n} \\ \vdots & & \vdots \\ \frac{1}{a_n+b_1} & \cdots & \frac{1}{a_n+b_n} \end{vmatrix} = \frac{\prod_{n \geqslant i > k \geqslant 1} (a_i - a_k)(b_i - b_k)}{\prod_{1 \leqslant i,k \leqslant n} (a_i + b_k)}.$$

Proof. We denote $D(n) = \det[1/(a_i + b_k)]_{1 \le i,k \le n}$. We subtract the last row of D(n) from each of the other rows, and then we can factor out from D(n) by $1, \ldots, n-1$ rows and $1, \ldots, n$ columns

$$D(n) = \begin{vmatrix} \frac{1}{a_1+b_1} & \cdots & \frac{1}{a_1+b_n} \\ \vdots & & \vdots \\ \frac{1}{a_{n-1}+b_1} & \cdots & \frac{1}{a_{n-1}+b_n} \\ 1 & \cdots & 1 \end{vmatrix} \cdot \frac{\prod_{i=1}^{n-1} (a_n - a_i)}{\prod_{i=1}^n (a_n + b_k)}.$$

Next we subtract the last column from each of the other columns, and extract the factors by $1, \ldots, n-1$ rows and $1, \ldots, n-1$ columns

$$D(n) = \begin{vmatrix} \frac{1}{a_1 + b_1} & \cdots & \frac{1}{a_1 + b_{n-1}} & \frac{1}{a_1 + b_n} \\ \vdots & & \vdots & \\ \frac{1}{a_{n-1} + b_1} & \cdots & \frac{1}{a_{n-1} + b_{n-1}} & \frac{1}{a_{n-1} + b_n} \\ 0 & \cdots & 0 & 1 \end{vmatrix} \cdot \frac{\prod_{i=1}^{n-1} (a_n - a_i)}{\prod_{i=1}^n (a_n + b_k)} \cdot \frac{\prod_{k=1}^{n-1} (b_n - b_k)}{\prod_{i=1}^{n-1} (a_i + b_n)}.$$

Therefore

$$D(n) = D(n-1) \cdot \frac{\prod_{k=1}^{n-1} (a_n - a_k)(b_n - b_k)}{(a_n + b_n) \prod_{k=1}^{n-1} (a_k + b_n)(a_n + b_k)},$$

by the induction we complete the proof.

Proof of AuxThm 2.4. Note that for $\lambda, \mu > -1/2$, we have

$$(x^{\lambda}, x^{\mu})_{L_2(0,1)} = \frac{1}{\lambda + \mu + 1}.$$

Then the theorem follows from

$$G(x^{\lambda_0}, \cdots, x^{\lambda_n}) = \frac{\prod_{n \geqslant i > k \geqslant 0} (\lambda_i - \lambda_k)^2}{\prod_{i=0}^n \prod_{k=0}^n (\lambda_i + \lambda_k + 1)},$$

and

$$G(x^r, x^{\lambda_0}, \dots, x^{\lambda_n}) = G(x^{\lambda_0}, \dots, x^{\lambda_n}) \cdot \frac{\prod_{k=0}^n (r - \lambda_k)^2}{(2r+1) \prod_{k=0}^n (r + \lambda_k + 1)^2}.$$

Theorem (Part of Theorem 1.1). Let $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \dots\}$ and $\lim_{n \to \infty} \lambda_n = \infty$. Then $\mathcal{M}(\Lambda_{\infty})$ is dense in $L_2[0,1]$ if and only if $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$.

Remark 2.5. Let $a_k > -1$, the convergence or divergence of infinity product can be related to infinity sum:

• $\prod_k (1 + a_k)$ converges if and only if $\sum_k \log(1 + a_k)$ converges.

• $\prod_k (1+a_k)$ diverges to 0 $(or +\infty)$ if and only if $\sum_k \log(1+a_k)$ diverges to $-\infty$ $(or +\infty)$.

Proof. We note that the space of algebraic polynomials \mathbb{P} is dense in $L_2[0,1]$. It is sufficient to show that

$$\forall r \in \mathbb{N} = \{0, 1, 2, \dots\}, \lim_{n \to \infty} E(x^r, \Lambda_n)_2 = 0 \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = \infty.$$

" \Leftarrow " Sufficiency. Suppose that $\sum_{n=1}^{\infty} \lambda_n^{-1} = \infty$ and $r \in \mathbb{N} \setminus \Lambda_{\infty}$. Note that $0 \in \Lambda_{\infty}$, thus $r \geqslant 1$. There exists an index k_0 s.t. $\lambda_k > r$ whenever $k \geqslant k_0$. Then

$$\lim_{n \to \infty} E(x^r, \Lambda_n)_2 = \frac{1}{\sqrt{2r+1}} \frac{\prod_{k=0}^{\infty} |r - \lambda_k|}{\prod_{k=0}^{\infty} |r + \lambda_k + 1|} = C(r, k_0) \frac{\prod_{k=k_0}^{\infty} \left(1 - \frac{r}{\lambda_k}\right)}{\prod_{k=k_0}^{\infty} \left(1 + \frac{r+1}{\lambda_k}\right)},$$

where

$$C(r, k_0) = \frac{1}{\sqrt{2r+1}} \prod_{k=0}^{k_0 - 1} \frac{|r - \lambda_k|}{|r + \lambda_k + 1|}.$$

Denote

$$S_1 = \sum_{k=k_0}^{\infty} \log\left(1 - \frac{r}{\lambda_k}\right), \ S_2 = \sum_{k=k_0}^{\infty} \log\left(1 + \frac{r+1}{\lambda_k}\right).$$

Then S_1 diverges to $-\infty$ (or the positive series $-S_1$ diverges to $+\infty$), if and only if the positive series

$$\sum_{k=k_0}^{\infty} \frac{r}{\lambda_k} = +\infty.$$

Similarly, S_2 diverges to ∞ if and only if the positive series

$$\sum_{k=k_0}^{\infty} \frac{r+1}{\lambda_k} = \infty.$$

Then $\lim_{n\to\infty} E(x^r, \Lambda_n)_2 = 0$ is obtained.

" \Rightarrow " Necessity. Otherwise, we suppose that $\sum_{k=1}^{\infty} \lambda_k^{-1} < \infty$. Then S_1 converges to a value ($\neq 0$), and S_2 converges to a value ($\neq 0$). Hence $\lim_{n\to\infty} E(x^r, \Lambda_n)_2 \neq 0$ leads to a contradiction. \square

Remark 2.6. The value $\lambda_0 = 0$ can be removed. In fact, let $\Lambda_{\infty} = \{0 < \lambda_1 < \dots < \lambda_n < \dots \}$ with $\lim_{n \to \infty} \lambda_n = +\infty$, then

$$\lim_{n \to \infty} E(1, \Lambda_n)_2 = 0 \iff \prod_{k=1}^{\infty} \left(1 - \frac{1}{\lambda_k + 1} \right) = 0 \iff \sum_{k=1}^{\infty} \log \left(1 - \frac{1}{\lambda_k + 1} \right) = -\infty$$

$$\iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k + 1} = +\infty \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = +\infty.$$

2.2.2 Case 2: $p = \infty$.

Our goal is to prove the (2.2) in [Lorentz (1996)], which is stated as following theorem:

AuxThm 2.6 (Theorem 5.5 in [Lorentz (1993)]). For r > 0, $\Lambda = \{\lambda_1, \lambda_2, \dots, \lambda_n\}$ with $\lambda_k > 0$, $k = 1, \dots, n$, we have

$$E(x^r, \Lambda)_{\infty} \leqslant \prod_{k=1}^n \frac{|r - \lambda_k|}{r + \lambda_k}.$$
 (3)

Proof. For any M > 0 (it will be determined later), we put $\bar{r} = Mr$ and $\mu_k = M\lambda_k$. For any coefficients $c_k \in \mathbb{R}$, we set

$$b_k = \frac{\bar{r} + 1/2}{\mu_k + 1/2} c_k, \ k = 1, 2, \dots, n,$$

and obtain

$$x^{\bar{r}+1/2} - \sum_{k=1}^{n} b_k x^{\mu_k + 1/2} = \left(\bar{r} + \frac{1}{2}\right) \int_0^x \left[t^{\bar{r}-1/2} - \sum_{k=1}^{n} c_k t^{\mu_k - 1/2} \right] dt.$$
 (4)

Since $\mu_k - 1/2 > -1/2$, $k = 1, \dots, n$, by AuxThm 2.4 we can select c_k to satisfy

$$\left\| t^{\overline{r}-1/2} - \sum_{k=1}^{n} c_k t^{\mu_k - 1/2} \right\|_{L^2(0,1)} = \frac{1}{\sqrt{2\overline{r}}} \prod_{k=1}^{n} \frac{|\overline{r} - \mu_k|}{\overline{r} + \mu_k}.$$

Then by Cauchy-Schwarz inequality and (4), we have $\forall x \in [0,1]$ and M>0

$$\left| x^{\bar{r}+1/2} - \sum_{k=1}^{n} b_k x^{\mu_k + 1/2} \right| \leqslant \left(\bar{r} + \frac{1}{2} \right) \sqrt{x} \left\| t^{\bar{r}-1/2} - \sum_{k=1}^{n} c_k t^{\mu_k - 1/2} \right\|_{L^2(0,1)},$$

which leads to

$$\left| x^{Mr} - \sum_{k=1}^{n} b_k x^{M\lambda_k} \right| \leqslant \frac{Mr + 1/2}{\sqrt{2Mr}} \prod_{k=1}^{n} \frac{|r - \lambda_k|}{r + \lambda_k}. \tag{5}$$

By choosing M = 1/(2r) and taking the transform $u = x^{1/(2r)}$ on (5), we have $\forall u \in [0,1]$

$$\left| u^r - \sum_{k=1}^n b_k u^{\lambda_k} \right| \leqslant \prod_{k=1}^n \frac{|r - \lambda_k|}{r + \lambda_k},$$

which give rise to (3).

Theorem (Part of Theorem 1.1). Let $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \dots\}$ and $\lim_{n \to \infty} \lambda_n = \infty$. Then $\mathcal{M}(\Lambda_{\infty})$ is dense in C[0,1] if and only if $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$.

Remark 2.7. $\lambda_0 = 0$ must be included in Λ_{∞} .

Proof. We note that \mathbb{P} is dense in C[0,1]. It is sufficient to show that

$$\forall r \in \mathbb{N} = \{0, 1, 2, \cdots\}, \ \lim_{n \to \infty} E(x^r, \Lambda_n)_{\infty} = 0 \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = \infty.$$

" \Leftarrow " Sufficiency. Suppose that $\sum_{n=1}^{\infty} \lambda_n^{-1} = \infty$ and $r \in \mathbb{N} \setminus \Lambda_{\infty}$. Note that $0 \in \Lambda_{\infty}$, thus $r \geqslant 1$. There exists an index k_0 s.t. $\lambda_k > r$ whenever $k \geqslant k_0$. Then

$$\lim_{n\to\infty} E(x^r, \Lambda_n)_{\infty} \leqslant \prod_{k=1}^{\infty} \frac{|r-\lambda_k|}{r+\lambda_k} = C(r, k_0) \frac{\prod_{k=k_0}^{\infty} \left(1-\frac{r}{\lambda_k}\right)}{\prod_{k=k_0}^{\infty} \left(1+\frac{r}{\lambda_k}\right)}, \text{ where } C(r, k_0) = \prod_{k=1}^{k_0-1} \frac{|r-\lambda_k|}{|r+\lambda_k|}.$$

Denote

$$S_1 = \sum_{k=k_0}^{\infty} \log\left(1 - \frac{r}{\lambda_k}\right), \ S_2 = \sum_{k=k_0}^{\infty} \log\left(1 + \frac{r}{\lambda_k}\right).$$

Then S_1 diverges to $-\infty$ and S_2 diverges to $+\infty$, leading to $\lim_{n\to\infty} E(x^r, \Lambda_n)_{\infty} = 0$.

" \Rightarrow " Necessity. Note that

$$E(x^r, \Lambda_n)_{\infty} \geqslant E(x^r, \Lambda_n)_2$$
.

Then $\forall r \in \mathbb{N}$, $\lim_{n \to \infty} E(x^r, \Lambda_n)_{\infty} = 0$ gives rise to $\lim_{n \to \infty} E(x^r, \Lambda_n)_2 = 0$, which leads to $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$.

2.2.3 Case 3: 2 .

Our goal is to prove the Theorem 2.2 in [Lorentz (1996)]:

Theorem 2.2 (Theorem 2.2 in [Lorentz (1996)]). Let $2 and <math>\Lambda = \{\lambda_0, \lambda_1, \dots, \lambda_n\}$ with distinct elements and $\lambda_k > -1/p$. For any $r > -\frac{1}{p}$, we have

$$E(x^r, \Lambda)_p \leqslant \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \prod_{k=0}^n \frac{|r - \lambda_k|}{r + \lambda_k + 2/p}.$$
 (2.4)

Lemma 2.1 (Lemma 2.1 in [Lorentz (1996)]). Let $1 \leqslant q and let <math>-\frac{1}{q} < \ell_0 < \ell_1 < \cdots < \ell_n$. For arbitrary real numbers a_0, a_1, \cdots, a_n and

$$b_k := \frac{1 + \ell_k + \frac{1}{p}}{1 + \frac{1}{p}} a_k, \quad 0 \leqslant k \leqslant n,$$

we have

$$\left\| x^{\frac{1}{q} - \frac{1}{p}} - \sum_{k=0}^{n} a_k x^{\ell_k + \frac{1}{q} - \frac{1}{p}} \right\|_p \leqslant \left(1 + \frac{1}{p} \right) \left\| 1 - \sum_{k=0}^{n} b_k x^{\ell_k} \right\|_q. \tag{2.3}$$

Proof. Let us denote $K := 1 + \frac{1}{p}$ and for $0 < x \le 1$

$$Q(x) := \sum_{k=0}^{n} b_k x^{\ell_k}, \quad h(x) := x^{\frac{1}{p}} (1 - Q(x)),$$
$$g(x) := K x^{\frac{1}{q} - 1 - \frac{2}{p}} \int_0^x h(t) dt.$$

One easily verifies that g is the function on the left hand side of (2.3). Our goal is to show

$$||g||_p \leqslant K||1 - Q(x)||_q$$
.

To achieve this goal, we employ Hölder type inequalities.

Hölder inequality: For any $1 \leq p, q \leq \infty$ that satisfy $\frac{1}{p} + \frac{1}{q} = 1$. Suppose that $f \in L_p(\Omega)$, $g \in L_q(\Omega)$ and $fg \in L_1(\Omega)$, then

$$||fg||_{L_1(\Omega)} \le ||f||_{L_p(\Omega)} ||g||_{L_q(\Omega)}.$$

Firstly, by Hölder's inequality, we have for $0 < x \le 1$,

$$|g(x)| \leq Kx^{\frac{1}{q}-1-\frac{2}{p}} \int_{0}^{x} |h(t)| dt \leq Kx^{\frac{1}{q}-1-\frac{2}{p}} \left(\int_{0}^{x} 1 dt \right)^{1-\frac{1}{q}} \left(\int_{0}^{x} |h(t)|^{q} dt \right)^{\frac{1}{q}}$$

$$= Kx^{-\frac{2}{p}} \left(\int_{0}^{x} |h(t)|^{q} dt \right)^{\frac{1}{q}} =: K \left(\int_{0}^{1} F(x,t) dt \right)^{\frac{1}{q}},$$

where

$$F(x,t) := \begin{cases} x^{-\frac{2q}{p}} |h(t)|^q, & \text{if } 0 \leqslant t < x, \\ 0, & \text{otherwise.} \end{cases}$$
 Note that $F(x,t) \in [0,1] \times [0,1].$

Hölder-Minkowski inequality (see [Bahouri (2011), p.4]) states:

Let (X_1, μ_1) and (X_2, μ_2) be two measure spaces and f be a nonnegative measurable function over $X_1 \times X_2$. For all $1 \leq q \leq p \leq \infty$, we have

$$\left\| \|f(x_1,\cdot)\|_{L_q(X_2,\mu_2)} \right\|_{L_p(X_1,\mu_1)} \le \left\| \|f(\cdot,x_2)\|_{L_p(X_1,\mu_1)} \right\|_{L_q(X_2,\mu_2)}.$$

Then by Hölder-Minkowski inequality, we have

$$\begin{split} \|g\|_{p} &\leqslant K \left[\int_{0}^{1} \left(\int_{0}^{1} F(x, t) dt \right)^{\frac{p}{q}} dx \right]^{\frac{1}{p}} = K \left\| \|F(x, \cdot)^{\frac{1}{q}} \|_{q} \right\|_{p} \\ &\leqslant K \left\| \|F(\cdot, t)^{\frac{1}{q}} \|_{p} \right\|_{q} = K \left[\int_{0}^{1} \left(\int_{0}^{1} F(x, t)^{\frac{p}{q}} dx \right)^{\frac{q}{p}} dt \right]^{\frac{1}{q}} \\ &= K \left[\int_{0}^{1} \left(\int_{t}^{1} x^{-2} |h(t)|^{p} dx \right)^{\frac{q}{p}} dt \right]^{\frac{1}{q}} \\ &= K \left[\int_{0}^{1} |h(t)|^{q} \left(\frac{1}{t} - 1 \right)^{\frac{q}{p}} dt \right]^{\frac{1}{q}} \leqslant K \left[\int_{0}^{1} |h(t)|^{q} \left(\frac{1}{t} \right)^{\frac{q}{p}} dt \right]^{\frac{1}{q}} \\ &= K \left[\int_{0}^{1} |t^{-\frac{1}{p}} h(t)|^{q} dt \right]^{\frac{1}{q}} = K \left[\int_{0}^{1} |1 - Q(t)|^{q} dt \right]^{\frac{1}{q}}. \end{split}$$

where the inequality holds since $0 < \frac{q}{p} < 1$ and $0 < \frac{1}{t} - 1 < \infty$ and

$$\left(\frac{1}{t} - 1\right)^{\frac{q}{p}} \leqslant \left(\frac{1}{t}\right)^{\frac{q}{p}}.$$

Remark 2.8. Note that q < p, then Lemma 2.1 is some kind of Inverse Inequality: Higher regularity norm bounded by lower regularity norm.

Proof of Theorem 2.2. To prove (2.4), our goal is to employ Lemma 2.1 and construct the formula

$$E(x^r, \Lambda)_p \leqslant \left\| x^{\frac{1}{2} - \frac{1}{p}} - \sum_{k=0}^n a_k x^{\ell_k + \frac{1}{2} - \frac{1}{p}} \right\|_p$$
, for some $\ell_k > -\frac{1}{2}$ and a_k .

To achieve this, for any a_k , $0 \le k \le n$, which will be determined later, we have

$$E(x^r, \Lambda)_p \leqslant ||x^r - \sum_{k=0}^n a_k x^{\lambda_k}||_p = \left[\int_0^1 \left(x^r - \sum_{k=0}^n a_k x^{\lambda_k} \right)^p dx \right]^{\frac{1}{p}}.$$

By a variable transform $x = y^{\rho}$, $\rho > 0$, which is invariant under the interval [0, 1] and ρ will be determined later, we have

$$E(x^{r}, \Lambda)_{p} \leq \left[\int_{0}^{1} \left(y^{\rho r} - \sum_{k=0}^{n} a_{k} y^{\rho \lambda_{k}} \right)^{p} \rho y^{\rho - 1} dy \right]^{\frac{1}{p}}.$$

$$= \rho^{\frac{1}{p}} \left\| y^{\rho r + \frac{\rho}{p} - \frac{1}{p}} - \sum_{k=0}^{n} a_{k} y^{\rho \lambda_{k} + \frac{\rho}{p} - \frac{1}{p}} \right\|_{p}.$$

Let $\rho r + \frac{\rho}{p} = \frac{1}{2}$, we obtain $\rho = \frac{p}{2(pr+1)}$. Let $\ell_k = \frac{p(\lambda_k - r)}{2(pr+1)} > -\frac{1}{2}$, it is easy to examine that $l_k + 1/2 > 0$, by Lemma 2.1, we have

$$E(x^{r}, \Lambda)_{p} \leq \left(\frac{p}{2(pr+1)}\right)^{\frac{1}{p}} \left\| y^{\frac{1}{2} - \frac{1}{p}} - \sum_{k=0}^{n} a_{k} y^{\ell_{k} + \frac{1}{2} - \frac{1}{p}} \right\|_{p}$$

$$\leq \left(\frac{p}{2(pr+1)}\right)^{\frac{1}{p}} \left(1 + \frac{1}{p}\right) \left\| 1 - \sum_{k=0}^{n} b_{k} y^{\ell_{k}} \right\|_{2}.$$
(6)

Since a_k is arbitrary, hence b_k is also arbitrary. Take the infimum on the right hand side of (6) over b_k , and by Theorem 2.4, we have

$$E(x^r, \Lambda)_p \leqslant \left(\frac{p}{2(pr+1)}\right)^{\frac{1}{p}} \left(1 + \frac{1}{p}\right) \prod_{k=0}^n \frac{|\ell_k|}{\ell_k + 1} = \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \prod_{k=0}^n \frac{|r - \lambda_k|}{r + \lambda_k + 2/p}.$$

Theorem (Part of Theorem 1.1). Let $\Lambda_{\infty} = \{0 = \lambda_0 < \lambda_1 < \dots < \lambda_n < \dots\}$ and $\lim_{n \to \infty} \lambda_n = \infty$. Then $\mathcal{M}(\Lambda_{\infty})$ is dense in $L_p[0,1]$, $2 , if and only if <math>\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$.

Proof. We note that \mathbb{P} is dense in $L_p[0,1]$. It is sufficient to show that

$$\forall r \in \mathbb{N} = \{0, 1, 2, \dots\}, \lim_{n \to \infty} E(x^r, \Lambda_n)_p = 0 \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = \infty.$$

" \Leftarrow " Sufficiency. Suppose that $\sum_{n=1}^{\infty} \lambda_n^{-1} = \infty$ and $r \in \mathbb{N} \setminus \Lambda_{\infty}$. Note that $0 \in \Lambda_{\infty}$, thus $r \geqslant 1$. There exists an index k_0 s.t. $\lambda_k > r$ whenever $k \geqslant k_0$. Then

$$\lim_{n \to \infty} E(x^r, \Lambda_n)_p \leqslant \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \frac{\prod_{k=0}^{\infty} |r - \lambda_k|}{\prod_{k=0}^{\infty} |r + \lambda_k + 2/p|} = C(r, k_0) \frac{\prod_{k=k_0}^{\infty} \left(1 - \frac{r}{\lambda_k}\right)}{\prod_{k=k_0}^{\infty} \left(1 + \frac{r + 2/p}{\lambda_k}\right)},$$

where

$$C(r, k_0) = \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \prod_{k=0}^{k_0 - 1} \frac{|r - \lambda_k|}{|r + \lambda_k + 2/p|}.$$

Denote

$$S_1 = \sum_{k=k_0}^{\infty} \log\left(1 - \frac{r}{\lambda_k}\right), \ S_2 = \sum_{k=k_0}^{\infty} \log\left(1 + \frac{r + 2/p}{\lambda_k}\right).$$

Then S_1 diverges to $-\infty$ and S_2 diverges to $+\infty$, leading to obtain $\lim_{n\to\infty} E(x^r, \Lambda_n)_p = 0$.

" \Rightarrow " Necessity. Note that

$$E(x^r, \Lambda_n)_p \geqslant E(x^r, \Lambda_n)_2.$$

Then $\forall r \in \mathbb{N}$, $\lim_{n \to \infty} E(x^r, \Lambda_n)_p = 0$ gives rise to $\lim_{n \to \infty} E(x^r, \Lambda_n)_2 = 0$, which leads to $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$.

Remark 2.9. The value $\lambda_0 = 0$ can be removed. In fact, let $\Lambda_{\infty} = \{0 < \lambda_1 < \dots < \lambda_n < \dots \}$ with $\lim_{n \to \infty} \lambda_n = +\infty$,

$$\prod_{k=1}^{\infty} \left(1 - \frac{2/p}{\lambda_k + 2/p} \right) = 0 \iff \sum_{k=1}^{\infty} \log \left(1 - \frac{2/p}{\lambda_k + 2/p} \right) = -\infty$$

$$\iff \sum_{k=1}^{\infty} \frac{2/p}{\lambda_k + 2/p} = +\infty \iff \sum_{k=1}^{\infty} \frac{1}{\lambda_k} = +\infty.$$

Then if $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$, we have $\lim_{n\to\infty} E(1,\Lambda_n)_p = 0$. Conversely, if $\lim_{n\to\infty} E(1,\Lambda_n)_p = 0$, which leads to $\lim_{n\to\infty} E(1,\Lambda_n)_2 = 0$, we have $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$.

2.2.4 Conclusion and remarks.

Let $2 \leq p \leq \infty$ and $\Lambda = {\lambda_k}_{k=0}^n$ with $\lambda_k > -1/p$. Then for any r > -1/p, we have

$$E(x^r, \Lambda)_p \leqslant \frac{1 + 1/p}{(2r + 2/p)^{1/p}} \prod_{k=0}^n \frac{|r - \lambda_k|}{r + \lambda_k + 2/p}.$$

A Variant of Dense Property.

(see also Section 5 of Chapter 11 in [Lorentz (1993)])

Let $C[0,+\infty]$ be the space of continuous functions on $[0,+\infty]$, which have a finite limit for $t\to\infty$. Exponential sums

$$\sum_{k=0}^{n} a_k e^{-\lambda_k t}$$

approximate arbitrarily closely each function $f \in C[0,+\infty]$ if and only if $\lambda_0 = 0$, $\lambda_k > 0$ for $k \ge 1$ and $\sum_{k=1}^{\infty} \lambda_k^{-1} = \infty$.

References

- [Lorentz (1996)] Lorentz G G, von Golitschek M, Makovoz Y. Constructive approximation: advanced problems[M]. Berlin: Springer, 1996.
- [Erdélyi (2001)] Erdélyi T, Johnson W B. The "Full Müntz Theorem" in $L_p[0,1]$ for 0 [J]. Journal D'Analyse Mathématique, 2001, 84(1): 145-172.
- [Almira (2007)] Almira J M. Muntz type theorems I[J]. arXiv preprint arXiv:0710.3570, 2007.
- [Agler (2022)] Agler J, McCarthy J. Asymptotic Müntz-Szász Theorems[J]. arXiv preprint arXiv:2206.12487, 2022.
- [Wang Renhong (1999)] Wang Renhong. Numerical Approximation (in Chinese)[M]. Higher Education Press, 1999.
- [Lorentz (1993)] DeVore R A, Lorentz G G. Constructive Approximation[M]. Springer-Verlag, 1993.
- [Bahouri (2011)] Bahouri H. Fourier Analysis and Nonlinear Partial Differential Equations[M]. Grundlehren der Mathematischen Wissenschaften, 2011, 343.
- [Adams (2003)] Adams R A, Fournier J J F. Sobolev spaces[M]. Elsevier, 2003.
- [Borwein (1995)] Borwein P, Erdelyi T. Polynomials and Polynomial Inequalities[M]. Springer Science & Business Media, 1995.
- [Powell (1981)] Powell M J D. Approximation theory and methods[M]. Cambridge university press, 1981.
- [Brezis (2011)] Brezis H. Functional analysis, Sobolev spaces and partial differential equations[M]. New York: Springer, 2011.